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(Article begins on next page)

1    **Reliability-based design for debris flow barriers**

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3    Vagnon, Federico

4    Department of Earth Science, University of Turin, Via Valperga Caluso 35, 10125, Turin, Italy

5    Corresponding author: federico.vagnon@unito.it, Tel: +39 0116705325

6

7    Ferrero, Anna Maria

8    Department of Earth Science, University of Turin, Via Valperga Caluso 35, 10125, Turin, Italy

9    anna.ferrero@unito.it

10

11    Alejano, Leandro R.

12    Department of Natural Resources and Environmental Engineering, University of Vigo, Galicia,

13    Spain

14    alejano@uvigo.es

## 15    **Abstract**

16    In the European Union since 2010, the design of any type of structures must comply with EN-1997  
17    Geotechnical Design (CEN 2004) (EC7) referring to engineering projects in the rock mechanics  
18    field. However, the design of debris flow countermeasures in compliance with EC7 requirements is  
19    not feasible: EC7 uses partial safety factors for design calculations, but safety factors are not  
20    provided for phenomena such as debris flows and rock falls. Consequently, how EC7 can be applied  
21    to the design of debris flow barriers is not clear, although the basic philosophy of reliability-based  
22    design (RBD), as defined in EN1990 (CEN 2002) and applicable to geotechnical applications, may  
23    be a suitable approach.

24    However, there is insufficient understanding of interactions between debris flows and structures to  
25    support RBD application to debris flow barrier design, as full-scale experimental data are very  
26    limited and difficult to obtain. Laboratory data are available but they are governed by scale effects  
27    that limit their usefulness for full-scale problems.

28    The article describes an analysis, using the first-order reliability method (FORM), of two different  
29    datasets, one obtained through laboratory experiments and the other reflecting historical debris flow  
30    events in the Jiangjia Ravine (China). Statistical analysis of laboratory data enabled a definition of  
31    the statistical distributions of the parameters that primarily influence debris flow and barrier  
32    interactions. These statistical distributions were then compared to the field data to explore the links  
33    between flume experiments and full-scale problems.

34    This paper reports a first attempt to apply RBD to debris flow countermeasures, showing how the  
35    choice of the target probability of failure influences the barrier design resistance value. An analysis  
36    of the factors governing debris flows highlights the applicability and limitations of EN1990 and  
37    EN1997 in the design of these rock engineering structures.

38

39    **Keywords**

40    Eurocode 7 (EC7); Reliability index; First-order reliability method (FORM); Partial safety factor;  
41    Debris flow; Mitigation design.

## 42 1. Introduction

43 Debris flows are extremely rapid gravitational movements that occur widely on Earth. They are  
44 among the most devastating landslide processes owing to their unpredictability, their total absence  
45 of premonitory signals, their high velocities and their long travel distances. Many mitigation  
46 strategies have been developed in recent years to reduce the associated risk, and both active and  
47 passive measures are used to reduce the magnitude and frequency of debris flows and to change the  
48 vulnerability of debris flow basins. Although passive measures (hazard mapping and correct land-  
49 use planning) are more advisable than active measures (protection structures), the latter are often  
50 essential in order to reduce risk (Jakob and Hungr 2005).

51 Common active measures can be classified as rigid measures – such as close-type check dams,  
52 open-type sabo dams and concrete-slit sabo dams – and flexible measures, mainly net barriers  
53 designed as a function of the deformation capability. Although very different in terms of  
54 components, drainage capacity and construction methodology, their main requirement is to  
55 counteract the impact forces underlying debris flow, dissipate its kinetic energy and totally or  
56 partially retain the flowing material.

57 The design of countermeasures is still an open issue. While there are many approaches to evaluating  
58 impact pressure (Hungr et al. 1984; Armanini and Scotton 1992; Hubl et al. 2009; Vagnon and  
59 Segalini 2016), uncertainty regarding flow characteristics (velocity and thickness) tends to be high  
60 and difficult to quantify (Jakob and Hungr 2005; Vagnon et al. 2015).

61 With this issue in mind, the Geotechnical Engineering Office of the Government of Hong Kong  
62 introduced the first technical basis for the design of standardized debris-resisting barrier modules to  
63 mitigate natural terrain landslide hazards (Sun et al. 2003). While its report analyses different debris  
64 flow run-out models and barrier types, there is no mention of the probability of failure of these  
65 structures. In 2009, the Austrian Standard Institute proposed the Österreichischen

66 Normungsinstituts Regeln (ONR) 24800 series to design torrent control structures. ONR 24802  
67 (2011) defines loading scenarios for debris flow protection structures, specifically providing  
68 information on limit state design and failure mode for check dams, as well as partial safety factors  
69 for structural (STR) and geotechnical (GEO) limit state actions.

70 When considering the design of debris flow barriers, uncertainties regarding all debris flow phases  
71 are difficult to quantify; consequently, since the degree of reliability is not evaluated, the probability  
72 of failure remains unknown.

73 The interaction between debris flow and barrier is only dealt with in passing in EN-1997  
74 Geotechnical Design (CEN 2004) (EC7), and although protection structures are widely used for  
75 mitigation purposes, there are no specific indications regarding their design. In previous works  
76 (Vagnon et al. 2016; Vagnon et al. 2017), the authors highlighted limitations in the applicability of  
77 EC7, and in particular the limit state design (LSD) approach to designing this type of structure due  
78 to the limited availability of experimental data. The set of proposed partial factors are clearly  
79 inadequate since they refer only to flow density and internal friction angle and neglect other  
80 relevant debris flow parameters such as flow velocity and thickness.

81 Uncertainties are considered in EC7: the concept of characteristic value introduced by the LSD  
82 approach allows a cautiously mean value to be selected, averaged over the failure surface and taking  
83 into account variability and uncertainties in the very definition of the parameter. However, spatial  
84 correlations between the same kind of parameters and cross-correlations between different  
85 parameters are still missing (Low and Phoon 2015). Many studies have demonstrated the presence  
86 of cross-correlations that are not entirely negligible, especially between soil parameters. Concerning  
87 debris flow, in a recent work, Vagnon and Segalini (2016) demonstrated a correlation between  
88 velocity and flow height.

89 For all the above reasons, the authors believe that a design approach based on a target reliability

90 index (Duncan 2000; Baecher and Christian 2003) could be a useful complementary tool in defining  
91 a uniform probability of failure for geotechnical structures. Reliability-based design (RBD) can  
92 provide additional insights into EC7 design and can be applied where partial factors have yet to be  
93 proposed (by EC7) to cover the uncertainties associated with less common parameters (Low and  
94 Phoon 2015), as is the case of debris flow countermeasures. Moreover, as stated by Duncan (2000),  
95 reliability calculations are a means for evaluating the combined effects of uncertainties and for  
96 distinguishing between conditions where uncertainties are very high, a clear example of which is  
97 evaluation of debris flow impact pressure.

98 RBD is widely used, especially in civil engineering, and has been applied to the study of slope  
99 stability (Li et al. 2016; Zhao et al. 2016; McGuire and VandenBerge 2017; Huang et al. 2018).  
100 EN 1990 (2002), the European standard that describes the basis for structural design, requires  
101 structures to be designed with an appropriate degree of reliability, which varies as a function of  
102 three reliability classes (RCs) for the ultimate limit state. The problem, however, is that there is no  
103 clear indication of the best class to choose and EC7, moreover, does not suggest any relationship  
104 between the RCs and geotechnical classes (Section 2.1 EC7). Normally, a reliability index greater  
105 than 3.8 for a 50-year reference period (corresponding to RC2) is recommended.

106 The purpose of this paper is to perform RBD for debris flow protection barriers and to propose a  
107 methodology for evaluating the probability of failure for such complex problems. Two databases,  
108 one obtained from laboratory experimental tests and one based on real events in the Jiangjia Ravine  
109 basin in China, are used as a basis for an analysis of the complementary relationship between EC7  
110 and RBD.

111 This paper, which, as far as we are aware, represents a first attempt to apply RBD to debris flow  
112 protection barriers, shows how the choice of a target probability of failure influences the resistance  
113 value of the barrier design. The analysis covers factors governing debris flow as well as variations –

114 as a function of the probability of failure – in partial safety factors computed using the Excel  
115 spreadsheet platform for **the first-order reliability method (FORM)** developed by Low and Tang  
116 (2007).

117

## 118 **2. FORM procedures**

119 Reliability analyses are commonly expressed by the Hasofer-Lind (1974) reliability index  $\beta$ , which  
120 can be related to probability of failure,  $P_f$ .  $P_f$  can be estimated as follows:

121

$$122 \quad P_f \approx 1 - \Phi(\beta) = \Phi(-\beta) \quad (1)$$

123

124 where  $\Phi$  is the normal cumulative probability function.

125 Since the reliability index is calculated by minimizing the quadratic form tangent to the limit state  
126 surface at the most probable failure point (Figure 1), defining  $\beta$  makes it possible to determine the  
127 coordinates of what is called the design point ( $x^*$ ). Physically denoted is the tangency of the  
128 expanding dispersion ellipsoid with the failure domain surface.

129

130 **Figure 1.** Illustration of the reliability index in a plane with two negatively correlated random  
131 variables.

132

133 While numerous methods to perform reliability analyses have been described, e.g., by Ditlevsen  
134 (1981), Ang and Tang (1984), Madsen et al. (1986), Low and Tang (1997), Haldar and Mahadevan  
135 (1999), Melchers (1999) and Baecher and Christian (2003), the most consistent approach is FORM,  
136 which is a useful spreadsheet-automated constrained optimization approach (Low and Tang, 2007).



137 In the spreadsheet, the equation for evaluating  $\beta$  is:

138

$$139 \quad \beta = \min_{x \in f} \sqrt{\vec{n}^T [R]^{-1} \vec{n}} \quad (2)$$

140

141 where  $\vec{n}$  is a dimensionless vector defined as  $\vec{n} = (x - \mu^N) / \sigma^N$ ,  $x$  is a vector representing the set of  
142 random variables,  $\mu^N$  and  $\sigma^N$  are the vectors of normal mean and normal standard deviation  
143 evaluated using Rackwitz–Fiessler equations (1978),  $R$  is the correlation matrix, and  $f$  is the failure  
144 domain.

145 For each value of  $n_i$  trialled by the Excel Solver, a short and simple Excel VBA code automates the  
146 computation of  $x_i$  from  $n_i$ , for use in the constraint performance function  $g(x) = 0$ , via  $x_i = F^{-1} \Phi[(n_i)]$ ,  
147 where  $\Phi$  is the standard normal distribution and  $F$  is the original non-normal distribution.

148 The use of Equation 2 is necessary because, as will be discussed in later sections, the leading  
149 variables in debris flow phenomena follow non-normal distributions.

150

### 151 **3. RBD versus EC7 design**

152 EC7 is based on LSD, a semi-probabilistic method in which partial factors are applied to  
153 characteristic parameter values in order to account for parameter uncertainty and so achieve designs  
154 with a certain target reliability (Figure 2).

155

156 **Figure 2.** EC7 limit state design: probabilities of actions and material resistance.

157

158 The aim underlying LSD, which is based on reliability analyses, is to provide structures with a  
159 uniform probability of failure (Figure 2). The fundamental principle is to verify that design

160 resistance is always greater than the effect of action. This verification can be done by following one  
161 of three different design approaches, described in detail in Section 2.4.7.3.4 of EC7 (EN 1997-  
162 1:2004). Broadly speaking, EC7 requires the use of partial safety factors aimed at reducing  
163 resistance and enhancing actions. While the efficacy of this approach has been demonstrated in civil  
164 engineering, its efficacy in the geotechnical field has raised many doubts, particularly in rock  
165 mechanics, where variability and uncertainty associated with materials (soil and rock) play a  
166 fundamental role (Harrison 2014; Lamas et al. 2014; Vagnon et al. 2020). Furthermore, in EC7 a  
167 number of geotechnical problems are not adequately covered, including debris flows and rock falls.  
168 The partial safety factor approach does not provide any information on the probability of failure of  
169 the designed structures and has never been investigated for debris flow protection purposes.

170 The above considerations are pertinent to understanding why an RBD analysis is required for  
171 certain complex geotechnical applications, including the design of debris flow protection structures.  
172 Some authors (Callisto 2010; Low and Phoon 2015) have highlighted how applying the same partial  
173 safety factors in problems with different levels of uncertainty may not result in the same target  
174 failure probability. By fixing the reliability index, however, the probability of failure remains the  
175 same, i.e., it is not dependent on the problem type and or the level of parametric uncertainty. Partial  
176 safety factors can be back-calculated from the RBD by fixing characteristic values for the random  
177 variables and by assessing the design point coordinates.

178 The dearth of data to perform statistical analyses may be considered the main limitation of an RBD  
179 approach. This is especially true in the case of debris flow, for which databases for the main  
180 parameters involved (velocity,  $v_f$ , thickness,  $h_f$ , and the dynamic coefficient,  $\alpha$ ) are difficult to  
181 obtain.

182 In sum, in the case of debris flow phenomena, RBD provides insights missing from EC7 design  
183 when statistical information on key parameters is available, when partial factors have not been

184 proposed and when input parameters are correlated.

185

#### 186 **4. Statistical analysis of laboratory and real debris flow motion characteristics**

187 As stated above, the main limitation of the RBD approach is the availability of data to conduct  
188 robust statistical analyses and to define the probability distribution of the parameters considered in  
189 the performance function. Evaluated below is the fit between probabilistic models and debris flow  
190 motion data, using a dataset of experimental laboratory tests performed by the authors (laboratory  
191 dataset) and a dataset of 139 real events that occurred in the Jiangjia Ravine basin in China (field  
192 dataset).

193 The laboratory dataset contains flow velocity and thickness values as well as the dynamic  
194 coefficients for 82 experimental laboratory flume tests (Figure 3) in which a debris flow was  
195 created by the rapid emptying of a hopper into the flume. Different material volumes (0.065 to  
196 0.075 m<sup>3</sup>) and different flume slopes (30° to 35°) were used in the experiments. Velocity, flow  
197 height and the impact force were recorded using four ultrasonic levels located along the centre line  
198 of the channel and four load cells installed directly on the barrier.

199 The dynamic coefficient is a dimensionless parameter used in hydrodynamic models to evaluate  
200 impact pressure on obstacles/structures. Dependent on the grain size distribution of the flow and  
201 barrier/obstacle characteristics (Vagnon and Segalini 2016), for the purposes of this research it was  
202 indirectly derived from experimental and field data using Hungr et al.'s hydrodynamic model  
203 (1984):

204

$$205 \quad \alpha = \frac{p_{measured}}{\rho v_f^2} \quad (3)$$

206

207 where  $p_{measured}$  is the impact pressure measured in Pa,  $\rho$  is the flow density in  $\text{kg/m}^3$ , and  $v_f$  is the  
208 impacting flow velocity in m/s.

209 A more detailed description of laboratory apparatus and instruments can be found in Vagnon and  
210 Segalini (2016).

211

212 **Figure 3.** Flume setup and location of measurement devices.

213

214 The field dataset includes thickness ( $h_f$ ), density ( $\rho$ ), channel width (B), duration (t) and velocity ( $v_f$ )  
215 values for 139 historical events that took place between 1961 and 2000 in the Jiangjia Ravine basin  
216 located in the Dongchuan area of Yunnan Province in China (Zhang and Xiong 1997; Kang et al.  
217 2006, 2007; Hong et al. 2015). This basin experiences numerous debris flow events each year (up to  
218 28) that cause great damage to local infrastructure (Hong et al. 2015). Debris flows, which mainly  
219 occur during the rainy season (June to September), lead to highly fractured rocks and colluvium  
220 being eroded and rapidly carried to the valley floor (Zhou and NG 2010).

221 An unparalleled record is available of long-term observations of this site by the Dongchuan Debris  
222 Flow Observation and Research Station (DDFORS), which set up a permanent monitoring station in  
223 the downstream area in the 1960s. Flow velocity is measured by a stopwatch in two marked  
224 sections along the gully, front head thickness is measured by a supersonic lever meter and surge  
225 density is measured by direct sampling of debris flows. The dynamic coefficient was back-  
226 calculated using Equation 3. Table 1 shows the main features of the datasets.

227

228 **Table 1.** Principal laboratory and field dataset features.

229

230 The raw data from the two datasets was used to perform a statistical analysis for the parameters  
231 listed in Table 2.

232  
233 **Table 2.** Main statistical parameters for the laboratory and field datasets.

234  
235 Each distribution was sorted into k-intervals in order to obtain the relative frequency of the real  
236 data. The following equation was used to evaluate the number of classes:

237  
238 
$$k = 2n^{0.4} \tag{4}$$

239  
240 where  $k$  is the number of classes and  $n$  is the dimension of the population data. For the laboratory  
241 and field datasets, the number of classes was, respectively, 12 and 14.

242 The basic idea behind this statistical analysis, in addition to defining probabilistic models for each  
243 parameter, was to evaluate the interchangeability of models between laboratory and field datasets.  
244 The probabilistic analysis was performed first for the laboratory measurements and then for the  
245 field measurements.

246 The statistical distribution of laboratory measurements for  $v_f$ ,  $h_f$  and  $\alpha$  were simulated using seven  
247 probabilistic models: normal, lognormal, exponential, Gumbel, generalized extreme value (GEV),  
248 Gamma and Weibull. Since there was no prior knowledge on debris flow phenomena, the suitability  
249 of each model for predicting distributions of  $v_f$ ,  $h_f$  and  $\alpha$  was not known. While the Gumbel and  
250 GEV distribution have been used in hydraulic analyses to evaluate the return period for a specific  
251 river flood height, there are no suggestions of their applicability to the debris flow field.

252 The goal was to verify which probability distributions best fitted the laboratory data and then try to

253 apply those distributions to the field data. The fit of each probabilistic model was assessed using  
254 two statistical goodness-of-fit (GoF) tests: Chi-square ( $\chi^2$ ) and Anderson–Darling (AD). The  
255 probabilistic model not rejected by both GoF tests was then used as input for the Low and Tang  
256 (2004) spreadsheet.

257 Table 3 lists the results of the GoF tests for the three considered variables,  $v_f$ ,  $h_f$  and  $\alpha$ . The results  
258 of GoF tests highlighted that: (i) the GEV model is suitable for simulating all three parameters, and  
259 (ii) the Gumbel model acceptably simulates the distributions of  $v_f$  and  $\alpha$ .

260 The described procedure is a first attempt to statistically analyse debris flow events. The analogy  
261 with other river processes, in which extreme value distributions are satisfactorily applied to describe  
262 rare events such as extreme floods, is undeniable.

263

264 **Table 3.** Laboratory measurements: two statistical goodness-of-fit test results for  $v_f$ ,  $h_f$  and  $\alpha$ .

265

266 Figure 4 shows a comparison between cumulative probability distributions for  $v_f$ ,  $h_f$  and  $\alpha$  and the  
267 corresponding predictive probabilistic model.

268

269 **Figure 4.** Laboratory data: comparison of cumulative probability distributions for measured and  
270 theoretically predicted  $v_f$  (a),  $h_f$  (b), and  $\alpha$  (c).

271

272 From the laboratory data it was observed that velocity, thickness and dynamic coefficient values  
273 might be approximated using a GEV distribution. However, since debris flow experimental tests are  
274 a scaled-down representation of the real phenomenon, presuming a GEV distribution (or any other  
275 distribution) might be unjustified without a comparison with real data. The authors verified,

276 following the same procedure as described above, whether this hypothesis could be confirmed using  
277 the Jiangija Ravine dataset of real values.

278 Table 4 and Figure 5 summarize the results of the statistical analysis of the field data. Concerning  
279  $v_f$ , the GEV distribution passed the Chi-square test but failed the AD test; however, Figure 5a  
280 clearly shows that there exists an acceptable approximation between the GEV and the cumulative  
281 distributions of the measured data, as the mean difference between the two curves is less than 10%.  
282 As for the dynamic coefficient  $\alpha$ , this could be approximated using both the lognormal and GEV  
283 distributions. Concerning flow thickness, the Gumbel, GEV and Weibull distributions satisfied all  
284 the criteria of the GoF tests. The hypothesis was therefore confirmed: the **GEV** properly describes  
285 the probability distributions of thickness and velocity in flow-like phenomena.

286

287 **Table 4.** Field measurements: two statistical goodness-of-fit test results for  $v_f$  and  $h_f$ .

288

289 **Figure 5.** Field data: comparison of the cumulative probability distributions for measured and  
290 theoretically predicted  $v_f$  (a),  $h_f$  (b) and  $\alpha$  (c).

291

292 The key point concerning the statistical treatment of debris flow events is that, while the scientific  
293 literature includes some examples of extreme value distributions satisfactorily applied to debris  
294 flow magnitude (Helsen et al. 2002; Marchi and D'Agostino 2004), no examples exist for flow  
295 characteristics due to a lack of monitoring data. However, the statistical analysis confirms that both  
296 laboratory and field parameter distributions can be approximated using a GEV distribution.

297

298 **5. RBD of debris flow barriers**

299 As described above, FORM requires the introduction of a performance function  $g(x) = 0$  that  
300 generally reflects the difference between resistances and the effects of actions.

301 In this research, the following equation was used:

302

$$303 \quad g(x) = R - \rho \alpha v_f^2 h_f B \quad (5)$$

304

305 where  $R$  is barrier resistance in N,  $\rho$  is flow density in  $\text{kg/m}^3$  (equal to  $1920 \text{ kg/m}^3$  and  $2155 \text{ kg/m}^3$ ,  
306 respectively, for laboratory and field data), and  $B$  is channel width in m (equal to  $0.39 \text{ m}$  and  $36 \text{ m}$ ,  
307 respectively, for laboratory and field data).

308 Equation 5 represents the difference between barrier resistance and flow thrust evaluated using  
309 Hungr et al.'s hydrodynamic model (1984). Dynamic impact force was calculated using the  
310 momentum equation, with the impacting mass considered to be a prism travelling with uniform  
311 velocity equal to mean flow velocity. Since lateral velocity variation was negligible at the flow  
312 front, the front thrust results were more significant. Flow density, assumed to be constant during the  
313 impact phase, was represented by a mean value for the solid and fluid components.

314 Low and Tang (1997) highlighted that correlation between variables produces a rotation of the  
315 dispersion hyperellipsoid, and consequently, a variation in the probability of failure. Table 2 shows  
316 that velocity and height flow and velocity and dynamic coefficient are negatively correlated, as  
317 discussed in Vagnon and Segalini (2016).

318 Since the barrier is manmade and built following engineering criteria, resistance probability was  
319 assumed to be normally distributed, with standard deviation equal to 3% of the mean.

320 EN1990 Annex C Table C1 gives a list of reliability index values,  $\beta$ , as a function of probability of  
321 failure,  $P_f$ . Using those values, a RBD approach to a debris flow rigid barrier is proposed, based on



an analysis of both laboratory and field datasets. In particular, the design points for each variable were identified and their distance from the corresponding mean was evaluated.

**Table 5.** Relationship between  $P_f$  and  $\beta$ .

Figure 6 depicts the Low and Tang (2007) FORM computational approach in the Microsoft Excel spreadsheet platform. The spreadsheet allows the value of the reliability index,  $\beta$ , to be minimized, starting from the main parameters that describe debris flow and their respective probabilistic distributions. Required for each distribution are the mean (Para1) and standard deviation (Para2). Microsoft Excel Solver automatically changes the  $x^*$  column in order to find the minimum value of  $\beta$ , by imposing two constraints: i)  $g(x)=0$  and ii) upper limits for the GEV distributions.

**Figure 6.** Determining the reliability index  $\beta$  and the coordinates of the design point  $x^*$  for a hypothetical rigid debris flow barrier.

In Figure 6, the column  $x^*$  represents the coordinates of the design point, i.e., the point where the four-dimensional equivalent dispersion ellipsoid is tangential to the limit state surface. These coordinates are the most probable failure combination for the debris flow parameters.

Listed in Table 6 as a function of the probability of failure are the combinations of design parameters for the laboratory and field data. At first sight, design resistance, velocity and dynamic coefficient values increase as the reliability index increases. Design thickness for laboratory data seems not to be influenced by the probability of failure; rather, considering the field data, it behaves similarly to the other design parameters. This behaviour is explained by smaller thickness variations

345 in the laboratory data compared to the field data.

346

347 **Table 6.** Design parameters evaluated for a reliability-based design approach as a function of  
348 reliability index values proposed in EN 1990 Annex C Table C1.

349

350 As discussed in relation to the statistical analysis, the reliability method is directly correlated with  
351 the partial safety factor concept introduced in EC7. In fact, the coordinates of the design point allow  
352 the partial safety factors to be evaluated, as, once the probabilistic distribution of the parameters is  
353 defined, the characteristic values can be back-calculated assuming the  $i^{\text{th}}$ -percentile of the  
354 probability distribution. The partial safety factor is the ratio between the characteristic value and the  
355 design parameter value.

356 Figure 7 shows flow barrier partial safety factor trends  $\gamma$  for each parameter, for laboratory data  
357 (circles) and field data (squares), as a function of the **probability of failure,  $P_f$** . Partial safety factors  
358 were calculated considering the 50<sup>th</sup>, 70<sup>th</sup> and 90<sup>th</sup> percentiles, indicated in black, dark grey and light  
359 grey, respectively.

360 Main findings can be summarized as follow:

- 361 - Generally, the higher the percentile value, the lower the partial safety factor value. The  
362 opposite occurs with partial safety factors for resistance, as these are reducing factors.
- 363 - Partial safety factors for resistance are independent from **probability of failure** values and are  
364 the same for both laboratory and field datasets (Figure 7a). This reflects a low degree of  
365 uncertainty in relation to barrier resistance evaluation.
- 366 - Even though the velocity and dynamic coefficient partial safety factors are different (Figures 7b  
367 and 7d), their trend is the same. In fact, those two figures suggest that characteristic values for  
368  $v_f$  and  $\alpha$  should be increased and that  $\alpha$  should be increased more than  $v_f$ .

369 - Significant differences are evident for partial safety factors for thickness, as for laboratory data,  
370 they remain constant and close to unity, whereas for field data, the trend is the same as for  
371 velocity and dynamic coefficient. The most plausible explanation is the greater variability in  
372 thickness measured in the field compared to in small-scale laboratory tests.

373

374 **Figure 7.** Partial safety factor dependence on resistance (a), velocity (b), thickness (c) and dynamic  
375 coefficient (d) as a function of probability of failure for laboratory data (circles) and field data  
376 (squares). Three percentiles were considered for each parameter probability distribution: 50<sup>th</sup>  
377 (black), 70<sup>th</sup> (dark grey) and 90<sup>th</sup> (light grey).

378

## 379 **6. Summary and conclusions**

380 Since the impact of debris flow against rigid and flexible protection structures is still not clearly  
381 understood, the design of countermeasures is problematic. First, design-related uncertainties  
382 complicate evaluation of the probability of failure, and second, further uncertainties arise in the  
383 assumptions that engineers are forced to make due to the lack of data. No clear guidelines as yet  
384 exist for the safe design of debris flow protection barriers. As pointed out elsewhere (Vagnon et al.  
385 2016, Vagnon et al. 2017), the EC7 LSD approach based on partial safety factors is not fully  
386 applicable, since the proposed partial safety factor set does not cover the main parameters  
387 associated with debris flow phenomena. We argue that structure interaction problems can be better  
388 analysed using a RBD approach that investigates the probability of failure associated with  
389 parameter variability.

390 The RBD approach to designing debris flow barriers described above complements the EC7 LSD  
391 approach and highlights the associated limitations and advantages. The main limitations are data  
392 availability and the possibilities for analysing data in a statistical framework. As mentioned, the

393 lack of monitoring data for real debris flow events forces assumptions to be made regarding  
394 statistical distribution.

395 In a more rigorous approach to this problem, the authors of this paper, drawing on laboratory and  
396 field data, selected the probability distributions that best fit the experimental data and verified the  
397 resulting probability distributions against the real dataset.

398 GEV has been demonstrated to be capable of simulating probabilistic distributions for flow height,  
399 velocity and thickness. The GEV distribution is frequently used to model flood event frequencies.  
400 Debris flows, we suggest, can be considered as a particular kind of riverine process and, on the  
401 basis of this analogy and the results of this research underpinned by rigorous statistical calculations,  
402 it should be possible to assume probabilistic extreme distributions for debris flows. However, to  
403 confirm or refute this assumption, further studies would need to be done using other datasets.

404 Regarding probability distributions, an interesting finding was that both laboratory data and field  
405 data follow the same statistical model, namely the GEV distribution, for all the variables. This  
406 further confirms the hypothesis that small-scale laboratory tests can simulate and obtain data for  
407 full-scale flow barrier design.

408 Another limitation of the RBD approach arises in the selected performance function: changing the  
409 impact model causes the value of  $\beta$  to change and this, in turn, causes the probability of failure to  
410 change. Sensitivity analyses would therefore be required in order to quantify the effect of the  
411 selected performance function.

412 The RBD approach allows back-calculated partial safety factors to be applied in the LSD method  
413 proposed by EC7. These partial safety factors have the advantage that they are associated with a  
414 known target failure probability. However, a question remains as to the universal meaning of partial  
415 safety factors for this type of geoengineering problems: the application of a set of partial safety  
416 factors does not allow determination of the associated probability of failure in the Limit State

417 Design (LSD) approach, contrary to the RBD approach. Moreover, there are not enough elements  
418 and accumulated experience, as in other geotechnical contexts (for instance, regarding the  
419 interactions between soils and foundations), to extend the partial safety factor approach to  
420 interactions between debris flows and barriers with some certainty of safety.

421 In conclusion, the RBD method provides insights into EC7 design for debris flow countermeasures  
422 and is a useful design approach for protection structures based on determining an associated  
423 probability of failure.

424

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427

428

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568 **Table 1.** Principal laboratory and field dataset features.

	Dataset	Apparatus/Basin	Material	Measured Physical Quantities	Dimension of the dataset	Range of variation of parameters
Laboratory experiments	Vagnon and Segalini, 2016	Steel flume 4 m long and 0.39 m wide in which the slope varies between 30° and 35°	Saturated sand with constant liquid concentration (0.4) and mixture density (1920 kgm <sup>-3</sup> ). Grain size distribution varies between 0.0001 and 5 mm	Flow velocity, impact height and impact forces recorded in real time during the experiment s	82 tests with different volumes and different slopes	v <sub>f</sub> : 1.16-6.74 ms <sup>-1</sup> h <sub>f</sub> : 0.01-0.07 m α: 0.44-3.44
Field measurements	Hong et al., 2015	Jiangjia Ravine basin (near Dongchuan city, China). Area 48.6 km <sup>2</sup> and mainstream length 13.9 km	Bulk density ranges from 1600 to 2300 kgm <sup>-3</sup> with fluid concentration ranging from 0.15 to 0.6. Solid particle dimensions vary between 0.001 and 100 mm	Channel width, flow velocity, impact height, density, duration and impact forces recorded in real time during debris flow events	139 events from 1961 to 2000	v <sub>f</sub> : 3-20 ms <sup>-1</sup> h <sub>f</sub> : 0.1-6.4 m α: 0.06-8

570 **Table 2.** Main statistical parameters for the laboratory and field datasets.

Parameter	Laboratory data			Field data		
	Value			Value		
	$v_f$ [m/s]	$h_f$ [m]	$\alpha$ [-]	$v_f$ [m/s]	$h_f$ [m]	$\alpha$ [-]
Mean ( $\mu$ )	3.67	0.05	1.21	10	1.6	1.36
Variance ( $\sigma^2$ )	1.28	0.0003	0.27	10	1.2	1.53
Standard deviation ( $\sigma$ )	1.13	0.02	0.52	3	1.1	1.24
Coefficient of variation (CV)	0.31	0.35	0.43	0.33	0.69	0.91
Asimmetry coefficient ( $\gamma$ )	0.69	-0.45	1.62	0.22	1.12	2.71
Maximum	6.74	0.07	3.44	20	6.4	8.01
Minimum	1.16	0.01	0.44	3	0.1	0.06
Coefficient of correlation v-h	-0.6			-0.6		
Coefficient of correlation v- $\alpha$	-0.5			-0.5		
Coefficient of correlation h- $\alpha$	-			-		
Number of experimental tests	82			139		
Number of classes (defined using Equation 3)	12			14		

571

572 **Table 3.** Laboratory measurements: two statistical goodness-of-fit test results for  $v_f$ ,  $h_f$  and  $\alpha$ .

Variable	Results		Probabilistic model						
			Normal	Lognormal	Exponential	Gumbel	GEV	Gamma	Weibull
$v_f$	Chi-square test	$\chi^2$	17.51	80.44	153.32	9.90	15.34	20.63	19.95
	Critical value	$\chi^2_{lim}$	16.92	16.92	18.31	16.92	15.51	16.92	16.92
	Suitability		NO	NO	NO	YES	YES	NO	NO
	AD test	$A^2$				0.196	0.458		
	Critical value	$A^2_{lim}$				0.461	0.461		
	Suitability					YES	YES		
$h_f$	Chi-square test	$\chi^2$	19.27	399.46	126.39	28.05	8.44	18.98	13.80
	Critical value	$\chi^2_{lim}$	16.92	16.92	18.31	16.92	15.51	16.92	16.92
	Suitability		NO	NO	NO	NO	YES	NO	YES
	AD test	$A^2$					0.279		0.917
	Critical value	$A^2_{lim}$					0.461		0.461
	Suitability						YES		NO
$\alpha$	Chi-square test	$\chi^2$	16.34	146.29	97.41	14.88	13.41	22.59	64.93
	Critical value	$\chi^2_{lim}$	16.92	16.92	18.31	16.92	15.51	16.92	16.92
	Suitability		YES	NO	NO	YES	YES	NO	NO
	AD test	$A^2$	2.65			0.283	0.440		
	Critical value	$A^2_{lim}$	0.46			0.461	0.461		
	Suitability		NO			YES	YES		

573

574 **Table 4.** Field measurements: two statistical goodness-of-fit test results for  $v_f$  and  $h_f$ .

Variable	Results		Probabilistic model						
			Normal	Lognormal	Exponential	Gumbel	GEV	Gamma	Weibull
$v_f$	Chi-square test	$\chi^2$	25.64	42.44	196.54	29.37	22.73	24.81	26.05
	Critical value	$\chi^2_{lim}$	24.72	24.72	26.22	24.72	23.21	24.72	24.72
	Suitability		NO	NO	NO	NO	YES	NO	NO
	AD test	$A^2$					0.93		
	Critical value	$A^2_{lim}$					0.461		
	Suitability						NO		
$h_f$	Chi-square test	$\chi^2$	26.88	39.53	33.93	8.21	8.21	12.78	8.63
	Critical value	$\chi^2_{lim}$	19.68	19.68	21.03	19.68	18.31	18.68	19.68
	Suitability		NO	NO	NO	YES	YES	YES	YES
	AD test	$A^2$				0.230	0.447	0.471	0.119
	Critical value	$A^2_{lim}$				0.461	0.461	0.461	0.461
	Suitability					YES	YES	NO	YES
$\alpha$	Chi-square test	$\chi^2$	96.99	18.79	59.47	67.33	12.99	45.13	44.30
	Critical value	$\chi^2_{lim}$	19.68	19.68	21.03	19.68	18.31	18.68	19.68
	Suitability		NO	YES	NO	NO	YES	NO	NO
	AD test	$A^2$		-13.91			-7.67		
	Critical value	$A^2_{lim}$		0.461			0.461		
	Suitability			YES			YES		

575

576 **Table 5.** Relationship between  $P_f$  and  $\beta$ .

$P_f$	1.00E-01	1.00E-02	1.00E-03	1.00E-04	1.00E-05	1.00E-06	1.00E-07
$\beta$	1.28	2.32	3.09	3.72	4.27	4.75	5.2

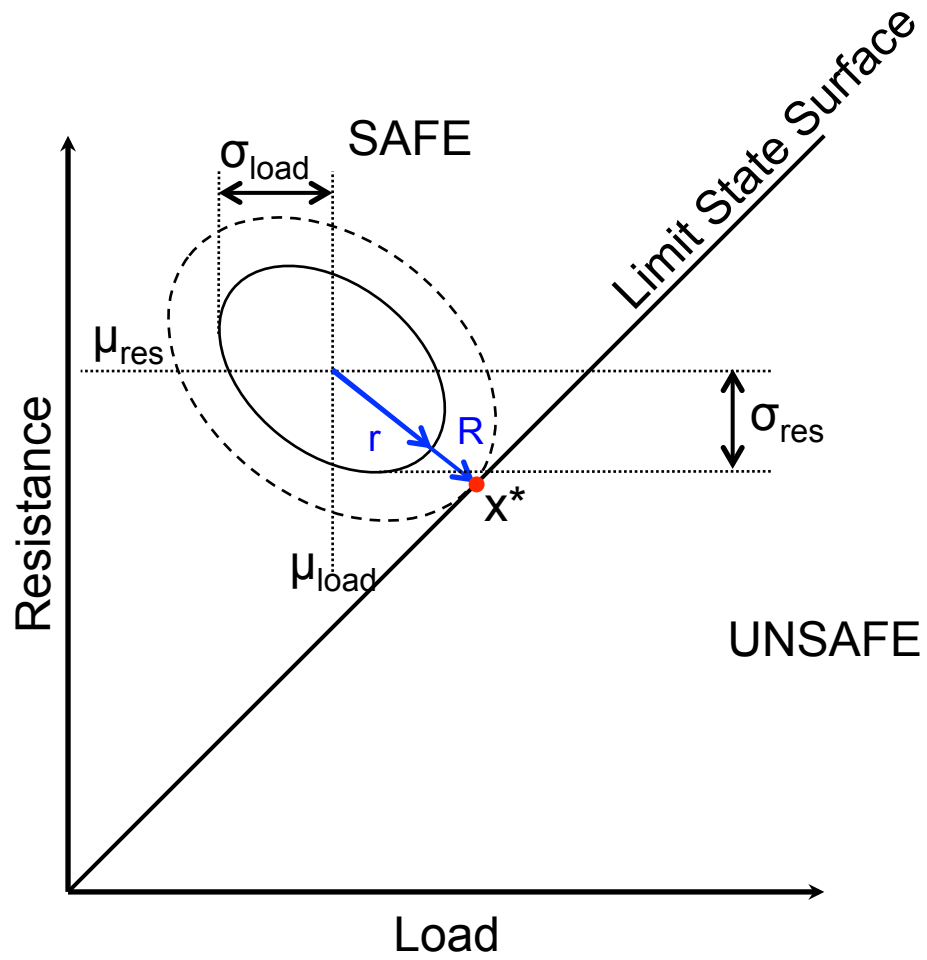
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578 **Table 6.** Design parameters evaluated after RBD approach as a function of reliability index values  
579 suggested by Annex C of EN 1990.

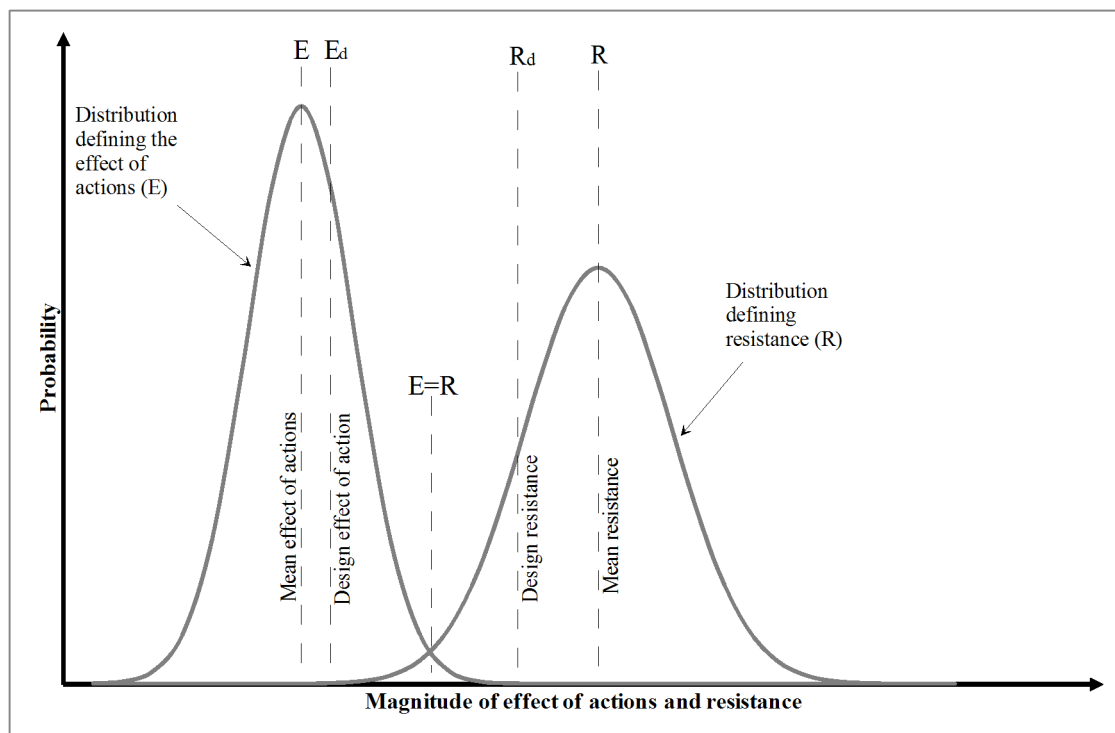
$\beta$ [-]	$P_f$ [-]	Laboratory data				Field data			
		$R^*$ [N]	$v_f^*$ [m/s]	$\alpha^*$ [-]	$h_r^*$ [m]	$R^*$ [N]	$v_f^*$ [m/s]	$\alpha^*$ [-]	$h_r^*$ [m]
1.28	1E-01	811.98	4.12	1.27	0.05	5.70E+07	12.17	2.22	2.24
2.32	1E-02	1219.21	4.72	1.46	0.05	1.60E+08	14.19	3.29	3.12
3.09	1E-03	1639.49	5.22	1.61	0.05	3.18E+08	15.57	4.28	3.96
3.72	1E-04	2089.45	5.31	1.98	0.05	5.35E+08	16.57	5.24	4.79
4.27	1E-05	2589.75	5.45	2.39	0.05	8.15E+08	17.35	6.20	5.63
4.75	1E-06	3129.86	5.52	2.77	0.05	1.16E+09	17.96	7.15	6.45
5.2	1E-07	3719.91	5.57	3.23	0.05	1.57E+09	18.47	8.12	7.30

580



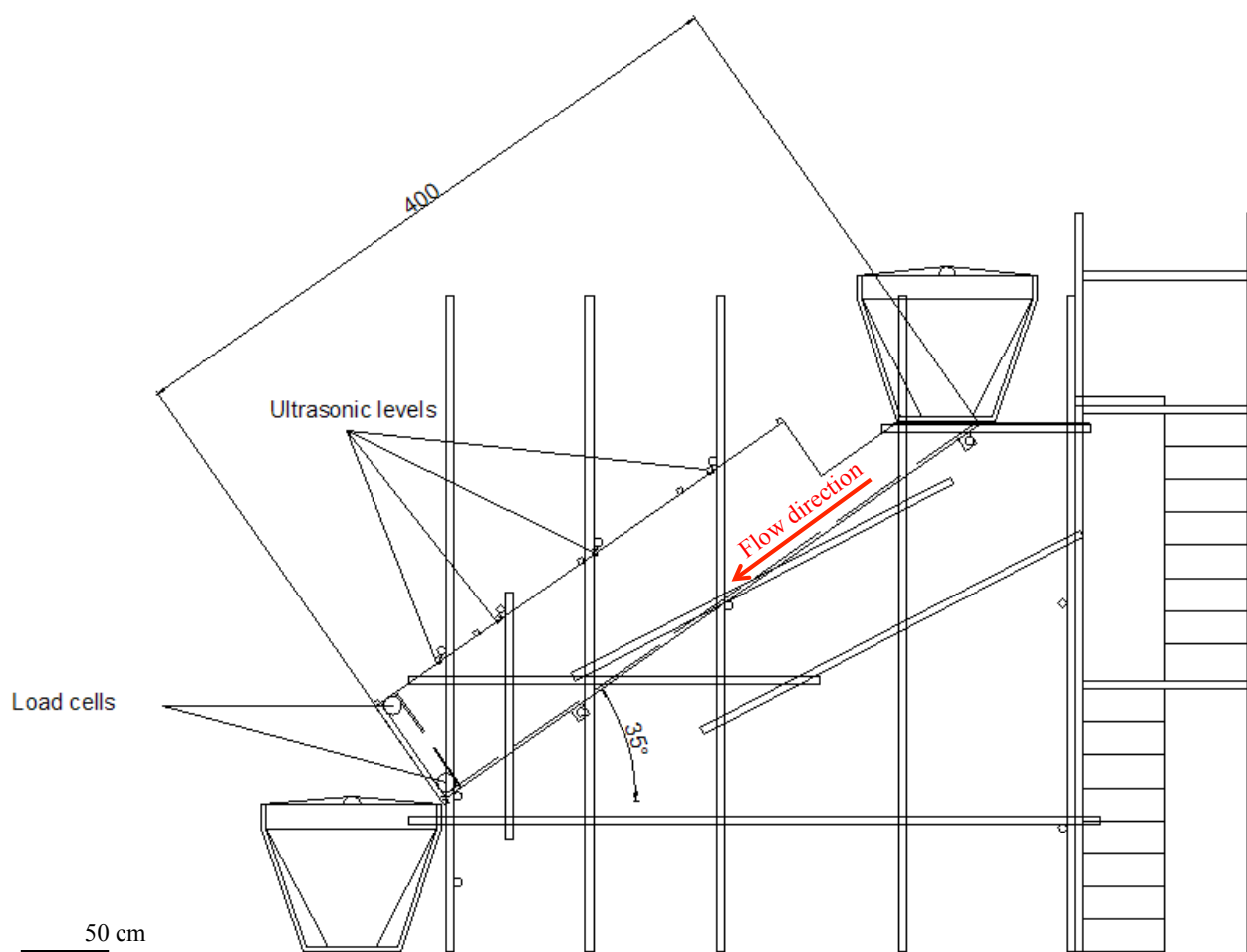
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583 **Figure 1.** Illustration of the reliability index in a plane with two negatively correlated random  
 584 variables.



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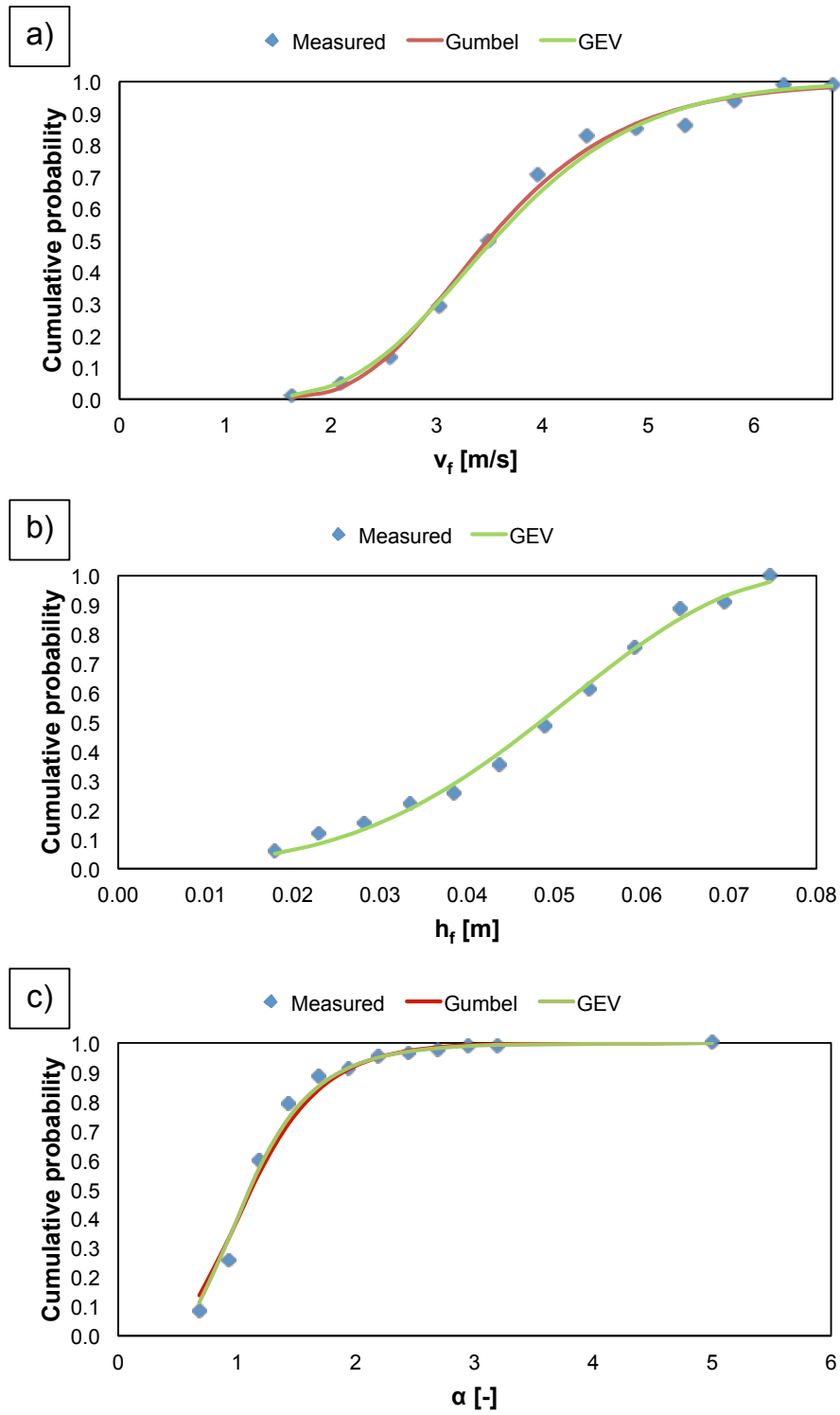
586 **Figure 2.** EC7 limit state design: probabilities of actions and material resistance.



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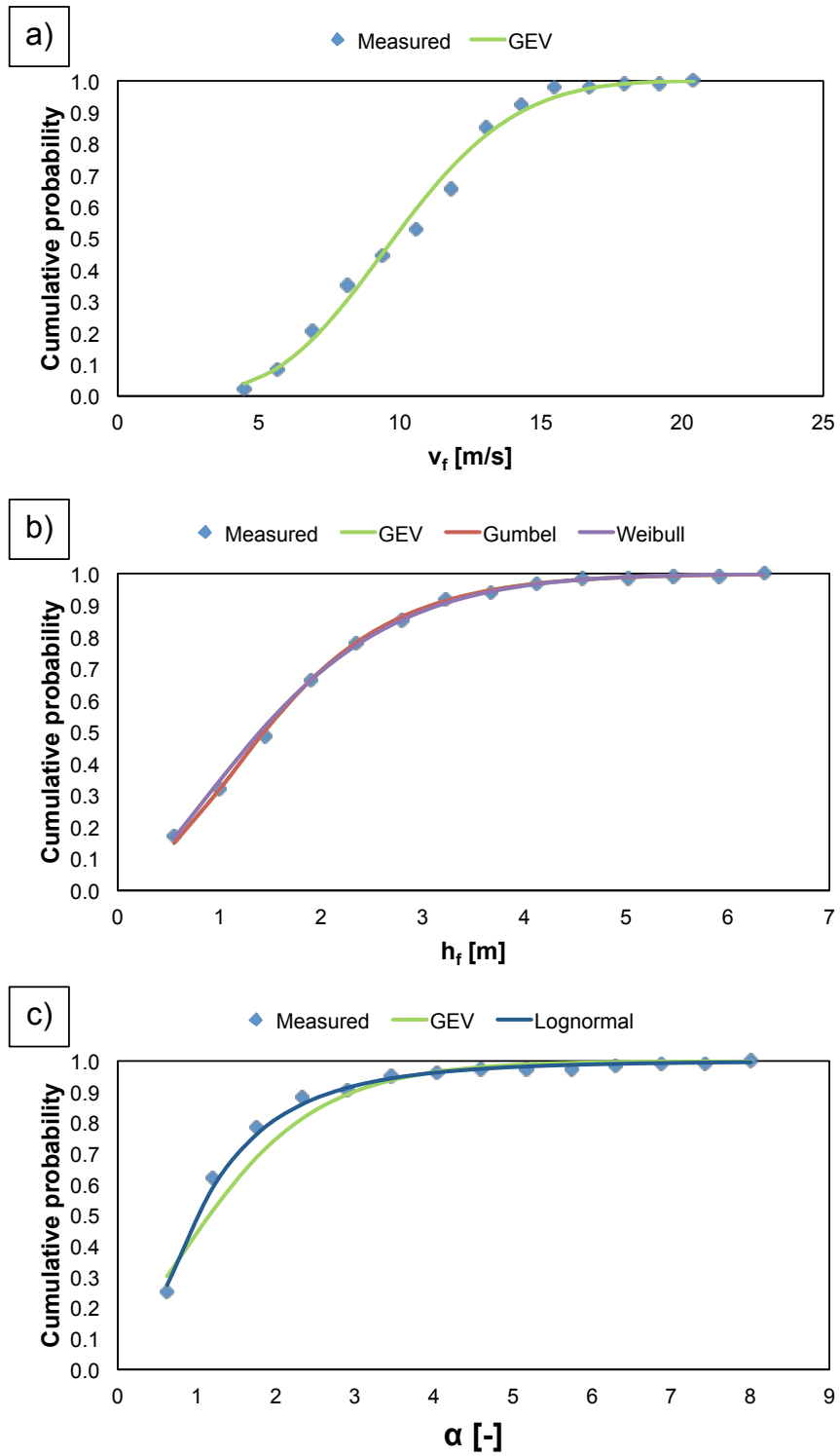
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**Figure 3.** Flume setup and location of measurement devices.



589

590 **Figure 4.** Laboratory data: comparison of cumulative probability distributions for measured and  
 591 theoretically predicted  $v_f$  (a),  $h_f$  (b), and  $\alpha$  (c).



592

593 **Figure 5.** Field data: comparison of the cumulative probability distributions for measured and  
 594 theoretically predicted  $v_f$  (a),  $h_f$  (b) and  $\alpha$  (c).

Distribution		Para1	Para2	$x^*$	$\mu^N$	$\sigma^N$
Normal	R	1570000000	4.71E+07	1.57E+09	1.57E+09	4.71E+07
GEV	vf	10	3	18.47	10.87	3.01
GEV	alfa	1.36	1.24	8.12	-3.12	3.43
GEV	hf	1.6	1.1	7.30	-2.03	2.97

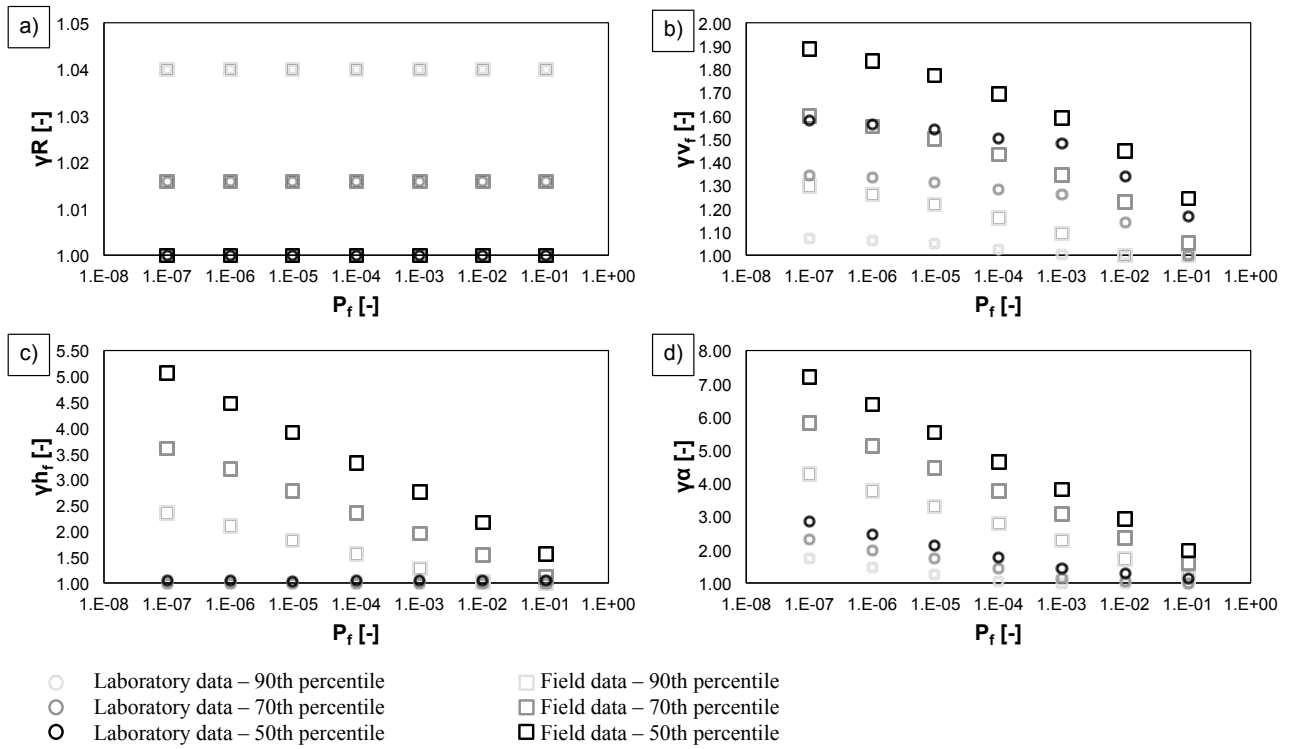
Correlation matrix [R]				n
1	0	0	0	-2E-14
0	1	-0.5	-0.6	3E+00
0	-0.5	1	0	3E+00
0	-0.6	0	1	3E+00

$g(x)$	$\beta$
0	5.20

Probability of failure
0.00001%

595

596 **Figure 6.** Determining the reliability index  $\beta$  and the coordinates of the design point  $x^*$  for a  
597 hypothetical rigid debris flow barrier.



598

599 **Figure 7.** Partial safety factor dependence on resistance (a), velocity (b), thickness (c) and dynamic  
600 coefficient (d) as a function of probability of failure for laboratory data (circles) and field data  
601 (squares). Three percentiles were considered for each parameter probability distribution: 50<sup>th</sup>  
602 (black), 70<sup>th</sup> (dark grey) and 90<sup>th</sup> (light grey).